A sharpness measure on automatically selected edge segments

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ABSTRACT

We address the problem of image quality assessment for natural images, focusing on No Reference (NR) assessment methods for sharpness. The metrics proposed in the literature are based on edge pixel measures that significantly suffer the presence of noise. In this work we present an automatic method that selects edge segments, making it possible to evaluate sharpness on more reliable data. To reduce the noise influence, we also propose a new sharpness metric for natural images.

Keywords: image quality assessment, no reference methods, sharpness.

1. INTRODUCTION

In the present article we address the problem of image quality assessment for natural images, focusing on No Reference (NR) assessment methods (i.e. where the original or ideal image is not available). For natural images, signal content and distortion may be not clearly separated, citing Sheik et al.:[1] 'all images are perfect, regardless of content, until distorted by acquisition, processing or reproduction'. In this way, we implicitly assume the presence of two signals: the content signal and the distortion signal. This philosophy assigns equal quality to all natural visual stimuli, and the task of NR Quality Assessment (QA) is reduced to blindly measure the distortion. In this work we focus on NR metrics for sharpness. In the available methods the sharpness measure is defined for each edge pixel and the final metric evaluation is obtained averaging all these values.[2] However, we have observed that in some cases this global measure is not representative of the real sharpness of the images. In fact, if the image contains different levels of depth field, this average operation can overestimate the edge spread. For example let us consider the images in Figure 1. The image on the left (Figure 1a) shows an object in the foreground visually sharped as desired by the photographer, while the background is blurred on purpose. Instead, the image on the right (Figure 1b) is overall blurred. Applying the metric defined by Marziliano et al.,[2] hereafter called Edge Spread Metric (ESM), to measure the sharpness, a similar score is obtained for both of these images (respectively 5.30 and 5.31). Another important issue in measuring sharpness is to obtain values stable with respect to noise. We have corrupted the two images of Figure 1 with a Gaussian noise on the intensity channel of 16 Gray Level of STandard Deviation (GLSTD). The corresponding images are reported in Figure 2. We have again applied the ESM and, as signal content and distortion are not clearly separated, the noise changes the sharpness estimation: the ESM measure for the image of Figure 1a goes from 5.30 to 2.64 of Figure 2a, while for Figure 1b it changes from 5.32 to 3.41 of Figure 2b. In the first row of Table 1, we have summarized the measures obtained applying the ESM metric globally for all the images of Figures 1 and 2. A possible approach to improve the faithfulness of the sharpness metrics is to manually select representative regions. To this end, we have recently proposed a modular No Reference Image Quality tool,[3] that permits to apply several NR metrics, not only globally but also locally. The local estimation assumes the presence of an expert operator that, using his/her prior knowledge, can select Regions Of Interests (ROIs) where the signal content only slightly affects the measure of the distortion. Within this framework, we have evaluated the sharpness of different ROIs for the images of Figures 1 and 2. The selected ROIs are shown with colored bounding boxes in Figure 2, (the same ROIs have been selected in Figure 1). In Table 1, second and third rows, we have listed the values of the ESM, evaluated locally on the edges found within the corresponding ROIs, in the four images considered. Comparing these values with those obtained globally, we can notice that in case of Figure 1b all the ROIs produce similar

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Table 1. ESM applied globally and locally

	Figure1a	*Figure1b*	*Figure2a*	*Figure2b*
GLOBAL	5.30	5.31	2.64	3.41
ROI 1	2.40	4.93	2.33	4.08
ROI 2	9.67	4.88	4.27	3.85

values, in accordance with the fact that the image is overall blurred, while for Figure 1a the values for the ROIs differ, corresponding to the intentionally different sharpness of the foreground and background. However the presence of noise (Figures 2a and 2b) affects the local measures. To visualize these results, in Figure 3 a bar diagram of Table 1 is shown.

Figure 1. a) Example of image where an object in the foreground is visually sharped as desired by the photographer. The background, instead, is blurred on purpose. b) Example of image overall blurred. Images courtesy from database.[4]

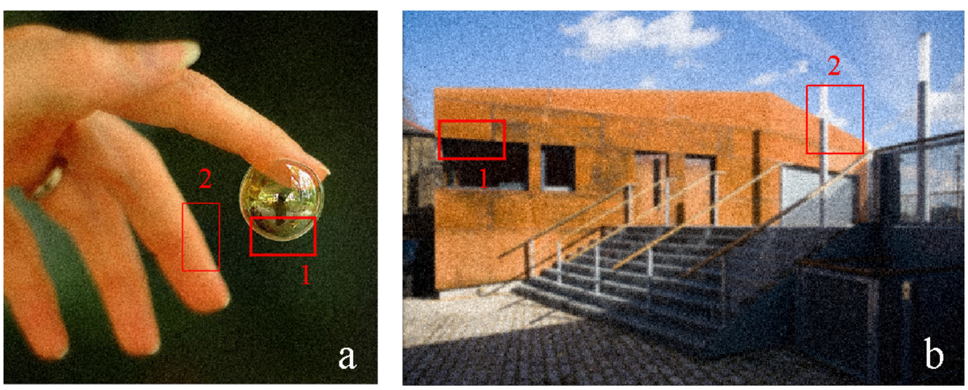


Figure 2. Noisy version of the images of Figure 1 with highlighted ROIs.

Addressing both the problems of selecting reasonable ROIs and making the measure less sensitive to noise level, in this work, we present an automatic method that selects representative edge segments, making possible to evaluate different metrics on more reliable data. To take into account the noise influence, we here also propose a sharpness metric for natural images, inspired by the slanted edge measure adopted by the Imatest[5] for synthetic images.

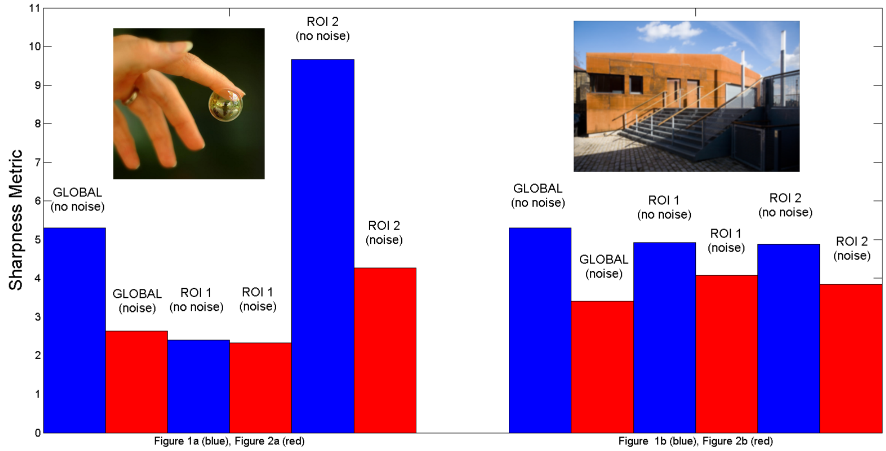


Figure 3. Bar diagram of Table 1

2. A SHARPNESS MEASURE ON AUTOMATICALLY SELECTED EDGE SEGMENTS

2.1 Automatic extraction of edge segments

In our proposal, the automatic selection of the more representative edge segments starts from a region-based segmentation algorithm. From the segmented image, we extract and collect all the boundaries between two adjacent regions as distinct segments. In our work we have used the Mean Shift Segmentation algorithm[6] to obtain a partition of an image into connected regions of pixels that are similar in appearance. Color image segmentation based on the Mean Shift algorithm is already popular in the computer vision community and several implementations exist.[7] An example of image segmented by the Mean Shift algorithm is shown in Figure 4 together with an example of what we called an edge segment (dotted line).

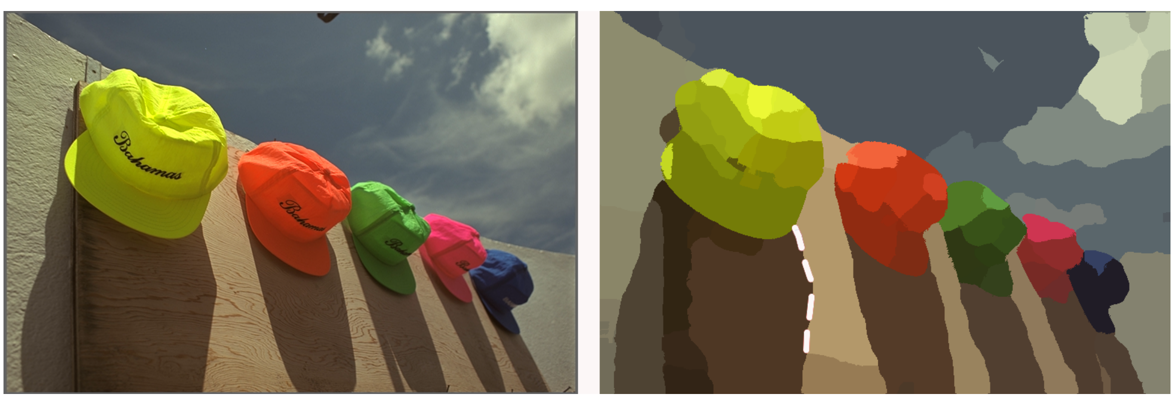


Figure 4. On the left an example image from the LIVE dataset,[8] and on the right the image segmented with the mean shift algorithm. An edge segment extracted is highlighted (dotted line).

2.2 Segment Spread Measure: SSM

Given an edge segment of N edge pixels, we extract the N profiles along the direction of the gradient of each edge pixel, (see Figures 5a and 5c). We estimate the N derivative functions corresponding to the N profiles using finite-differences and collect the N Gaussian functions that fit them (see Figures 5b and 5d). The mean Gaussian function (red and highlighted lines in Figures 5b and 5d) is computed and adopted to model these profiles. The standard deviation of this Gaussian is the spread (sharpness) estimation of the considered segment. The length of the profiles depends on the maximum edge spread we want to measure. In this work, taking into account the

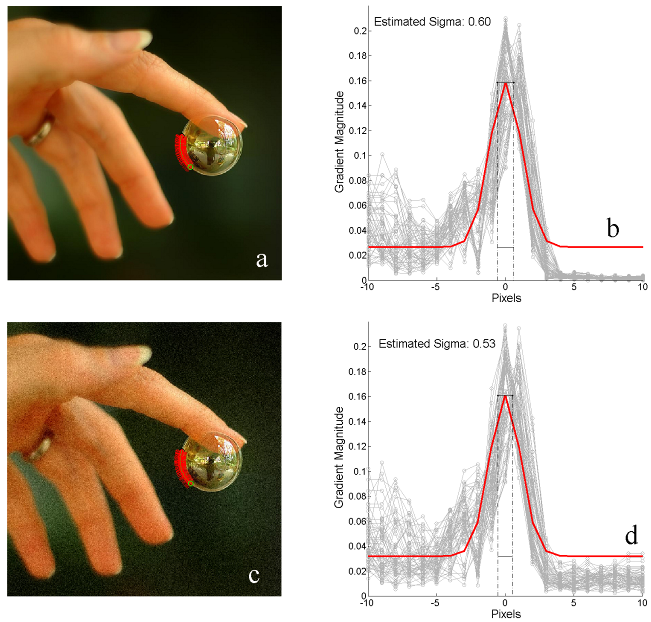


Figure 5. Estimated segment spread. (a) One of the segments extracted from Figure 1a and (c) one of the segments extracted from Figure 2a. (b) The Gaussian functions that fit the gradient of each profile for the segment highlighted in (a); the corresponding Gaussian functions for the profiles in (c). The estimated edge spread of the considered segment corresponds to the standard deviation of the mean Gaussian function, red highlighted lines in (b) and (d), respectively.

limited dimensions of the images considered in our experiments (768 x 512 pixels), we have considered profiles of 21 pixels. This permits a reliable estimation of a spread value less than 5 pixels. Given a reliable segment, we have a redundant information about the edge spread over the N collected profiles,therefore we expect the estimation of this spread to be more stable with respect to noise.

To select the segments on which evaluating the sharpness of the image, we consider the following features:

- The length of the segment;
- The average contrast of the segment, i.e. the mean of the module of the gradients of the edge pixels;
- The fitting error, i.e. the MSE between the N Gaussian functions of the profiles and the mean Gaussian function that models them.

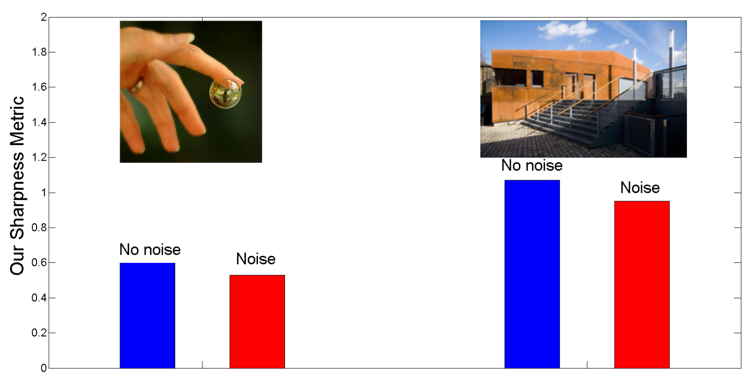


Figure 6. SSM applied to the original images (Figure 1) and to their noisy versions (Figure 2).

We select the segments with contrast greater than 0.3, fitting error smaller than 0.03 and length greater than 30 pixels. These threshold values have been found empirically. Let us assume that P segments have been selected

Table 2. Regression parameters for SSM and EES. A: slope, B: Intercept

	SSM		ESM	
Name	A	B	A	B
N0	1.04	-0.10	0.29	-0.45
N1	1.10	-0.10	0.32	-0.77
N2	1.13	-0.03	0.34	-0.82

using the above procedure. We collect the corresponding P spread estimations, and we extract the median of this distribution. This median is the finally SSM value assigned to the image.

Coming back to the example images of the Introduction, we applied the SSM to the images of Figures 1 and 2. For the original image depicted in Figure 1a and its noisy version (Figure 2a) the SSM are respectively 0.6 and 0.53. While for images of Figures 1b and 2b, we have obtained SSM values of 1.07 and 0.95 respectively. Figure 6 summarizes our results: the sharpness metric here proposed produces two different values for the two images. In agreement with our final goal, the values are more stable in the presence of noise.

3. RESULTS AND DISCUSSION

We have performed our experiments on three datasets defined starting from the LIVE database.[8] The LIVE database contains a set of 145 images with different levels of blurriness, obtained applying a Gaussian filtering with sigma varying from $\sigma = 0.4192$ to $\sigma = 15.00$. We test our measure on these images to recover the sigmas of the filters applied. Our three datasets are composed as follows:

- $N0$ is the original LIVE dataset of 145 images;
- $N1$ consists of the 145 images of $N0$, plus the $N0$ dataset corrupted by a Gaussian noise with 16 gray levels of standard deviation (16 GLSTD) on the three channels, for a total of 290 images;
- $N2$ consists of the 290 images of $N1$, plus the $N0$ dataset corrupted by a Gaussian noise with 32 gray levels of standard deviation (32 GLSTD) on the three channels, for a total of 290+145=435 images.

We have extended the LIVE sets defining the $N1$ and $N2$ datasets to test the stability of our SSM metric with respect to high levels of noise. In order to compare our metric with existing metrics in the literature, we have considered the ESM, since it has been proved to be a reliable metric[9] in the presence of blurriness. We have already shown in the Introduction, ESM strongly suffers the presence of noise. In particular this measure in presence of noise underestimates the actual blur of the edge. This is due to the procedure adopted by the ESM to estimate the edge spread, which measures the distance between minimum and maximum gray level values nearest to the edge point, along the gradient direction. Applying ESM to N1 and N2 datasets, we have obtained a constant value for all the images corrupted by high noise levels. Thus, to permit a fair metric comparison on the N1 and N2 datasets, we have modified the ESM introducing a pre-processing step, which consists in a noise reduction, obtained with a Gaussian filtering. This filter was optimized for each of the N0, N1 and N2 datasets to reduce the MSE error between the ESM and the known applied sigma. Hereafter when we refer to the ESM values we intend the spreads estimated on the images previously smoothed. Our method does not apply this pre-processing.

We have correlated the known applied sigmas with the estimated spreads obtained by both the SSM and the ESM. In order to analyze the results, we have performed a first order polynomial regression on the estimated values of both metrics. In Table 2 the slopes and intercepts obtained for the two metrics and for each of the three datasets are reported. Note that in the case of our measure the polynomials for all the datasets are very close to the diagonal.

With the parameters setting given in Section 2.2, our metric was unable to estimate the blurriness of images with high level of blur. An example of these images are reported in Figure7. In Table 3 we have reported the number of images for which our metric was not able to provide a measure with respect to the level of blurriness,

Table 3. The number of images where our metric was not able to provide a measure, with respect to the level of blurriness and to the total of images with the same blurriness.

	No response		
Applied Sigma	N0	N1	N2
5.83	1/2	3/4	5/6
7.66	4/4	8/8	12/12
11.33	2/2	4/4	6/6
15.00	1/1	2/2	3/3

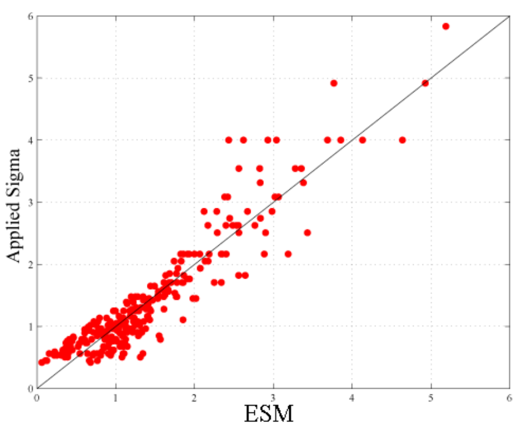
divided by the number of images with the same blurriness in the dataset considered. From this Table, we can see that the total of images with no SSM response are 8, 17, 26 for the N0, N1 and N2 datasets respectively.

Figure 7. Example of images where our metric does not produce a measure. (a) image smoothed with $\sigma = 7.66$ and (b) image smoothed with $\sigma = 11.33$

We have thus decided to remove all these images from the datasets to compare the performance of the ESM and the SSM. In Figure 8 we have reported the scatter plots of the estimated sigmas, versus the applied sigmas for both ESM and SSM. Our predictions are less spread with respect to the diagonal line than those obtained with ESM. Finally the results obtained in terms of MSE between the estimated sigmas and the known applied blurriness are reported in Table 4 for both metrics and with respect to the three datasets. Our metric outperforms the ESM on all the datasets, independently of the noise level, as clearly indicated by the percentage of improvements.

Table 4. Results in terms of MSE between the estimated sigmas and the known applied blurriness for both metrics and with respect to the three datasets.

Name	Dataset	Cardinality	MSE SSM	MSE ESM	Improvements
N0	No noise	145	1.7	2.7	37%
N1	N0 + 16 glstd	145×2	3.6	5.7	36%
N2	N1 + 32 glstd	145×3	7.7	9.2	16%



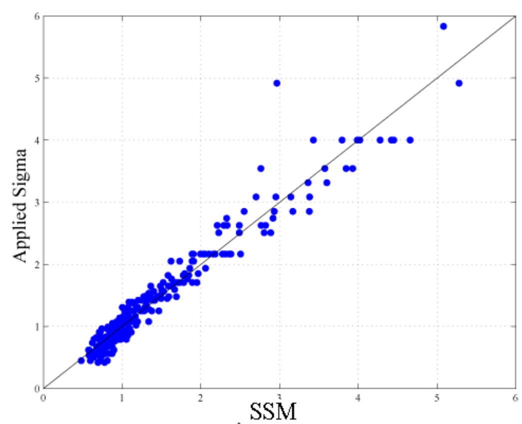


Figure 8. Scatter plots of the estimated sigmas, versus the applied sigmas for both ESM (a) and SSM (b)

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